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IIT Gandhinagar

August 2, 2025

$$\epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \dots \\ \epsilon_N \end{bmatrix}_{N \times 1}$$

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$$\epsilon^T \epsilon = \sum_i \epsilon_i^2$$

2.

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3. For a scalar s

$$s = s^T$$

4. Derivative of a scalar s wrt a vector θ

$$\theta = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_N \end{bmatrix}$$

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5. If A is a row-vector $(1 \times n \text{ matrix})$. and θ is a column-vector $(n \times 1)$ matrix. and $A\theta$ is a scalar.

Example

$$egin{aligned} heta &= egin{bmatrix} heta_1 \ heta_2 \end{bmatrix}_{2 imes 1} \ & A = egin{bmatrix} A_1 & A_2 \end{bmatrix}_{1 imes 2} \ & A heta_{1 imes 1} = A_1 heta_1 + A_2 heta_2 \end{aligned}$$

$$\frac{\partial A\theta}{\partial \theta} = \begin{bmatrix} \frac{\partial}{\partial \theta_1} (A_1\theta_1 + A_2\theta_2) \\ \frac{\partial}{\partial \theta_2} (A_1\theta_1 + A_2\theta_2) \end{bmatrix} = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix}_{2 \times 1} = A^T$$

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$$Z = X^{T}X = \begin{bmatrix} a^{2} + c^{2} & ab + cd \\ ab + cd & b^{2} + d^{2} \end{bmatrix}_{2\times 2}$$

6. Assume Z is a matrix of format X^TX , then $\frac{\partial}{\partial \theta}(\theta^TZ\theta)=2Z^T\theta$

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Z has a property $Z_{ij} = Z_{ji} \implies Z^T = Z$

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$$\theta^{T}Z\theta = e\theta_{1}^{2} + 2f\theta_{1}\theta_{2} + g\theta_{2}^{2}$$

The term $\theta^T Z \theta$ is a scalar.

$$\frac{\partial}{\partial \theta} \theta^{\mathsf{T}} \mathsf{Z} \theta = \frac{\partial}{\partial \theta} (\mathbf{e} \theta_1^2 + 2f \theta_1 \theta_2 + \mathbf{g} \theta_2^2)$$

$$= \begin{bmatrix} \frac{\partial}{\partial \theta_1} (\mathbf{e} \theta_1^2 + 2f \theta_1 \theta_2 + \mathbf{g} \theta_2^2) \\ \frac{\partial}{\partial \theta_2} (\mathbf{e} \theta_1^2 + 2f \theta_1 \theta_2 + \mathbf{g} \theta_2^2) \end{bmatrix}$$

$$= \begin{bmatrix} 2\mathbf{e} \theta_1 + 2f \theta_2 \\ 2f \theta_1 + 2\mathbf{g} \theta_2 \end{bmatrix} = 2 \begin{bmatrix} \mathbf{e} & \mathbf{f} \\ \mathbf{f} & \mathbf{g} \end{bmatrix} \begin{bmatrix} \theta_1 \\ \theta_1 \end{bmatrix}$$

$$= 2\mathbf{Z} \theta = 2\mathbf{Z}^{\mathsf{T}} \theta$$

 An rxc matrix as a set of r row vectors, each having c elements; or you can think of it as a set of c column vectors, each having r elements.

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- An rxc matrix as a set of r row vectors, each having c elements; or you can think of it as a set of c column vectors, each having r elements.
- The rank of a matrix is defined as (a) the maximum number of linearly independent column vectors in the matrix or (b) the maximum number of linearly independent row vectors in the matrix. Both definitions are equivalent.

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- If r is greater than c, then the maximum rank of the matrix is c.

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- What is the rank?
- r = c =. Thus, rank is ≤ 3
- Row 3 can be written as: 3 times Row 1 + 2 times Row
 1. Thus, Row 3 is linearly dependent on Row 1 and 2.
 Thus, rank(A)=2

What is the rank of

$$X = \left[\begin{array}{rrrr} 1 & 2 & 4 & 4 \\ 3 & 4 & 8 & 0 \end{array} \right]$$

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Since *X* has fewer rows than columns, its maximum rank is equal to the maximum number of linearly independent rows. And because neither row is linearly dependent on the other row, the matrix has 2 linearly independent rows; so its rank is 2.

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Below, with an example, we illustrate the relationship between a matrix and its inverse.

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Below, with an example, we illustrate the relationship between a matrix and its inverse.

$$\begin{bmatrix} 2 & 1 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 0.8 & -0.2 \\ -0.6 & 0.4 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

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Not every square matrix has an inverse; but if a matrix does have an inverse, it is unique.